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Short-Term Reversals and the Efficiency of Liquidity Provision

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Abstract

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We present a model where the magnitude of return reversals depends on the number of informed investors as well as the number of active but uninformed investors that play a market making role. Consistent with the model, return reversals are temporarily higher following declines in the number of active institutional investors. By using stock price declines over the previous one and two quarters as instruments for unanticipated declines in active investors, we get much stronger reversals. We also show that the magnitudes of the reversals as well as their relation to prior stock price declines are lower in the post-2000 period, which is consistent with active uniformed investors (e.g., high frequency traders) reacting more quickly to changes in the number of informed investors in the more recent period.

1 Introduction

The structure of U.S. equity markets has changed considerably over the past 20 years. Most notably, barriers to entry in the liquidity provision business have eroded. Indeed, with the introduction of decimalization and electronic order processing the roles of the traditional liquidity providers, e.g., NYSE specialists and Nasdaq market makers, have been largely replaced by what have become known as high frequency traders (see, for example Hendershott, Jones, and Menkveld, 2011).

Consistent with the inventory based market microstructure models, e.g., Stoll (1978) and Grossman and Miller (1988), the increased competitiveness of the market making sector has substantially decreased the magnitude of return reversals observed in the U.S. stock market.[1] To illustrate this, Panel A of Table 1 (discussed in more detail later in the paper) reports the returns of the Jegadeesh (1990) return reversal strategy for samples of large, medium, and small market capitalizations in periods before and after 2000. To be more specific, the table reports the returns of portfolios that are long stocks that performed very poorly in the previous month and are short stocks that performed very well. As these results illustrate, the magnitude of the return reversals have declined for each size category. Indeed, except for the micro-cap stocks, the Jegadeesh strategy earns insignificant returns on average in the more recent period.

Panel B of Table 1 reports magnitudes of industry-adjusted return reversals in the pre- and post-2000 periods. As shown in Hameed and Mian (2013), these reversals are stronger than non-industry-adjusted ones. These reversals also decline substantially for all but the micro-cap stocks in the post-2000 period, suggesting that for at least

[1] Conrad, Kaul, and Nimalendran (1990), Jegadeesh and Titman (1995), and Kaniel, Saar, and Titman (2008) discuss how market microstructure phenomena such as inventory control effects can cause reversals. The inventory theory of price formation has been elucidated by Stoll (1978), Ho and Stoll (1983), O'Hara and Oldfield (1986), Grossman and Miller (1988), and Spiegel and Subrahmanyam (1995).

the large stocks, the provision of liquidity in the recent period is relatively efficient.

To better understand the provision of liquidity in the pre- and post-2000 periods we develop a model where liquidity is provided by two groups of active and risk averse traders. The first group represents traditionally informed traders, who observe fundamental information that is correlated with cash flows. The second group represents high frequency traders or market makers, who are uninformed about fundamentals, but make trades based on their knowledge of the price process. Consistent with Grossman and Stiglitz (1980), Kyle (1985), and others, the model also includes random liquidity demanders or noise traders, whose actions influence both prices and expected rates of return.

Because the active investors in this model are risk averse, the random liquidity demands of the noise traders generate negative serial correlation in stock returns. The magnitude of this negative serial correlation decreases with an exogenous increase in the number of agents in either of the active-trader groups. The intuition is straightforward. An increase in active traders increases the availability of risk averse investors who can absorb the shocks generated by the noise or liquidity trades. Hence, the decline in the magnitude of return reversals in the post-2000 period that corresponds with an increase in market making activity (i.e., the introduction of high frequency traders) is consistent with the model.

We expand our model by allowing endogenous entry by the uninformed market makers, but initially keep the number of informed investors fixed. In this setting, a decrease in the cost of entry into the market making business increases entry and reduces the magnitude of the return reversals. Moreover, since informed investors also implicitly provide liquidity in this model, fewer market makers enter when the number of active informed investors increases.

The more interesting implication arises when we further extend the model to allow for exogenous shocks to the number of informed investors. While we do not directly model this, the shocks to the number of informed investors could come from shocks to either the costs or benefits of becoming informed. Regardless of the cause, an anticipated negative shock to informed participation results in an offsetting change in participation by market makers, and hence, only minor changes in the expected magnitude of return reversals.[2] However, as we show, an unanticipated decrease in informed participation, which cannot be immediately offset by market maker participation, does lead to a temporary increase in the magnitude of return reversals.

To empirically investigate our model's implications, we look directly at changes in the number of active institutional investors that hold each stock in our sample. The implicit assumption is that the number of institutions holding a stock is a proxy for the number of informed investors that actively follow and trade the stock. We show that for each size group, the magnitude of return reversals is higher for those stocks that experience a decline in the number of institutions holding their stock during the previous quarter.

Although these findings are consistent with our model, the estimated relation between return reversals and changes in institutional ownership is relatively weak. The weakness of these results, however, may be due to endogeneity and measurement issues that can distort the inferences from the above test. For example, anticipated changes in liquidity may influence the portfolio choices of active investors. In addition, changes in active institutional ownership may be anticipated, and the model predicts that a change in the magnitude of the reversals arises from unanticipated rather than anticipated changes in the number of informed investors. Hence, a test of our model requires an instrument for the unanticipated change in informed investor participation.

[2]As we discuss later, because the risk of the stock (conditional on the market price) will change when the number of informed investors change, return reversals can change. This is likely to be a second order effect.

The particular instruments we consider are stock returns over each of the previous four quarters. Stock returns are presumably unanticipated, and as we show, the number of active institutional investors does indeed decline following large negative stock return realizations. In addition to the endogenous liquidity considerations mentioned above, this decline could be due to window-dressing concerns, viz. Ritter and Chopra (1989), and Asness, Liew, and Stevens (1987), which might deter the inclusion of distressed stocks in institutional portfolios.[3]

Consistent with the prediction of our model, the profitability of the monthly return reversal strategies is substantially larger if returns in the prior one and two quarters are strongly negative. However, returns three and four quarters in the past have no reliable relation to the magnitude of the return reversal, which is consistent with our prediction of a temporary effect. Indeed, consistent with our model, in the post-2000 period, there is evidence of return reversals for the past one quarter losers even in the sample of large stocks that do not exhibit evidence of unconditional return reversals. However, there is no reliable relation between returns and future reversals that go beyond one quarter in the post-2000 period, which is consistent with the hypothesis that recent innovations facilitate the entrance of increased market making capacity in response to a decline in informed investors in the recent period.

It should be noted that although our interpretation is unique, we are not the first to consider the role of informed investors as liquidity providers. Indeed, our model is very close to Grossman and Stiglitz (1980) and the result that an increase in the number of informed investors reduces the magnitude of negative serial correlation follows directly from their model. However, Grossman and Stiglitz assume that the number of uninformed active investors is exogenous and focuses on the entry choice of informed

[3]Negative stock returns can also ensue from institutional selling that is prompted by unfavorable information. With short-selling constraints, institutions have less incentive to actively collect information on stocks that they do not own, so any event that prompts institutional selling is likely to lead to decreased market making capacity and increased contrarian profits.

investors. In contrast, we take the number of informed investors as exogenous as focus our attention on the endogenous entry of active uninformed investors who act as market makers.[4]

In addition, the models of Kaniel and Liu (2006), and Goettler, Parlour, and Rajan (2009) both imply that informed investors with long-lived private information will be sufficiently patient to use limit orders and thus supply liquidity. However, in contrast to these papers which focus on the incentives of the already informed to provide liquidity, or on the incentive of the uninformed to become informed, our focus is on the incentives of uninformed investors to trade actively (as market makers) and how this incentive interacts with the number of informed investors.

The paper is organized as follows: Section 2 presents the theoretical model that motivates our empirical tests. Section 3 describes our data and presents the empirical results, and Section 4 concludes the paper. All proofs, unless otherwise stated, appear in Appendix A.

2 The Model

2.1 The Stock Market

We model the stock price of a single firm that is born at date 0; investors trade the stock at date 1, and the firm's cash flows, which are realized at date 2, are expressed as follows,

$$F = \theta + \epsilon. \tag{1}$$

The variables θ and ϵ represent exogenous shocks; ϵ is not revealed until date 2, but θ can be observed by informed investors at date 1. These variables have zero mean

[4]Campbell, Grossman, and Wang (1993) also present a model of reversals caused by the risk aversion of market makers who absorb the order flow of outsiders. However, their model does not allow for endogenous entry of market makers and does not differentiate between anticipated and unanticipated shifts in the mass of informed agents.

and are mutually independent and normally distributed.

Following Grossman and Stiglitz (1980) we assume there are two types of optimizing active investors. There are masses m of informed agents and n of uninformed "market-makers," each with negative exponential utility with risk aversion R. The first group can be viewed as hedge funds, mutual funds and other investors that actively collect fundamental information about firm cash flows. These investors learn the realization of the shock θ perfectly after date 0 and prior to trade at date 1. The second group can be viewed as high frequency traders and other quantitative hedge funds that do not have access to fundamental information but try to make money from short-term price movements.

We assume that the shares which active investors trade are in zero net supply on average. The model is thus consistent with the existence of "passive" investors that simply hold the market portfolio, and almost never trade. However, these passive investors may be subject to exogenous liquidity shocks that affect the supply of shares available to the informed and uninformed investors that we model. We represent this additional demand of "liquidity traders" by z (or supply by $-z$), which is normally distributed with mean zero, and independent of all other random variables.[5] Throughout the paper we denote the variance of any generic random variable, η, by v_η.

The number of active investors, both m and n, are initially assumed to be determined exogenously; however, we will later relax this assumption and consider a case where the mass of market-makers is endogenous. One interpretation is that we will be considering conditions under which formerly passive investors choose to expend resources to actively monitor market conditions.

[5]The analysis is unchanged if we model z as an shock to the informed agents' endowment.

2.2 Demands

Let the subscripts I and U denote the informed and uninformed, respectively. Further, let W_i and ϕ_i, $i = \{I, U\}$, respectively denote the wealth and information sets of the two classes of agents. Each agent solves

$$\max E[-\exp(-RW_i)|\phi_i].$$

Since (as we will show) W_i is normally distributed in equilibrium as are the information sets ϕ_i, each agent maximizes

$$\max E(W_i|\phi_i) - 0.5\ R\ \mathrm{var}(W_i|\phi_i). \tag{2}$$

Let x_i denote the demand of agent i and P the market price. Then $W_i = (F - P)x_i$. It follows from solving (2) that the demand of each informed agent is

$$x_I = \frac{E(F|\theta, P) - P}{R\ \mathrm{var}(F|\theta, P)} = \frac{\theta - P}{Rv_\epsilon},$$

and that of each uninformed agent is

$$x_U = \frac{E(F|P) - P}{R\ \mathrm{var}(F|P)} = \frac{\mu - P}{R\ \mathrm{var}(F|P)}.$$

2.3 Equilibrium

Denote $v \equiv \mathrm{var}(F|P) = v_\epsilon + \mathrm{var}(\theta|P)$. The market clearing condition is

$$mx_I + nx_U + z = 0,$$

or

$$m\frac{\theta - P}{Rv_\epsilon} + n\frac{\mu - P}{Rv} + z = 0. \tag{3}$$

Let

$$\mu \equiv a_1\theta + a_2 z. \tag{4}$$

The rational expectations equilibrium of the model is derived in the Appendix, which provides analytic expressions for a_1, a_2, and v, and proves the following proposition.

Proposition 1 *The closed-form expression for the price P is given by*

$$P = H_1\theta + H_2 z, \tag{5}$$

where

$$H_1 = \frac{m[m^2 v_\theta + mnv_\theta + R^2 v_\epsilon v_z(v_\epsilon + v_\theta)]}{m^3 v_\theta + m^2 n v_\theta + mR^2 v_\epsilon v_z(v_\epsilon + v_\theta) + nR^2 v_\epsilon^2 v_z}, \tag{6}$$

and

$$H_2 = \frac{Rv_\epsilon H_1}{m}. \tag{7}$$

2.4 Return Predictability

Note that the date 0 price is not stochastic since the information and participation shocks are realized only at date 1. The serial covariance of price changes can therefore be expressed as $C \equiv \mathrm{cov}(F - P, P)$. We denote the corresponding serial correlation by ρ. Straightforward calculations lead to the following proposition:

Proposition 2 1. *The serial covariance of price changes, C, is given by*

$$C = -\frac{R^2 v_\epsilon^2 v_z[m^2 v_\theta + mnv_\theta + R^2 v_\epsilon v_z(v_\epsilon + v_\theta)][m^2 v_\theta + R^2 v_\epsilon v_z(v_\epsilon + v_\theta)]}{[m^3 v_\theta + m^2 n v_\theta + mR^2 v_\epsilon v_z(v_\epsilon + v_\theta) + nR^2 v_\epsilon^2 v_z]^2} \tag{8}$$

and is always negative.

2. *The absolute magnitude of the serial correlation in price changes, $|\rho|$, is decreasing in m, and n, the masses of informed agents and market makers, respectively.*

3. *The serial correlation ρ goes to zero as $n \to \infty$ or as $m \to \infty$.*

The negative serial covariance of price changes is a standard result; an unanticipated increase (decrease) in liquidity trades reduces (increases) the stock's risk premium since the change in holdings by these traders must be held by risk averse active traders who demand risk premiums. An increase (decrease) in the risk premium decreases (increases) the date 1 price, thereby decreasing (increasing) the expected date 2 return. The magnitude of these return reversals depends on both the risk aversion and the mass of the active investors. In particular, a decrease in the mass of either informed agents or market makers reduces the risk-bearing capacity of the market, thus increasing the magnitude of the reversal in asset returns. If the mass of either of these agents increases arbitrarily, in the limit, risk-bearing capacity of the market goes to infinity and the serial correlation goes to zero.

It should also be noted that H_2 captures the price impact of the noise trades, and the losses of the noise traders are given by

$$E[(P-F)z] = H_2 v_z.$$

The following results on H_2 are easily derived from (7) and are stated without proof.

Proposition 3 *1. The liquidity cost of trades is decreasing in the mass of market makers, n.*

2. As $n \to \infty$, the liquidity cost tends to

$$\frac{mRv_\epsilon v_\theta}{m^2 v_\theta + R^2 v_\epsilon^2 v_z},$$

a strictly positive quantity.

3. The liquidity cost is increasing in the mass of informed agents, m, if and only if

$$\begin{aligned} - \quad & Rv_\epsilon[m^4 v_\theta^2 + 2m^3 n v_\theta^2 + m^2 v_\theta\{n^2 v_\theta + 2R^2 v_\epsilon v_z(v_\epsilon + v_\theta)\} \\ + \quad & 2mnR^2 v_\epsilon v_\theta^2 v_z - R^2 v_\epsilon^2 v_z\{n^2 v_\theta - R^2 v_z(v_\epsilon + v_\theta)^2\}] > 0. \end{aligned}$$

Since an increase in the mass of market makers increases the risk-bearing capacity of the market, liquidity costs decline. Liquidity costs remain finite even as the mass of market makers increases without bound, because of the effect of information asymmetry on liquidity costs. An increase in the mass of informed agents has an ambiguous effect on liquidity costs because, on the one hand, an increase in this mass increases the risk bearing capacity (which tends to decrease liquidity costs), but on the other hand, implies more adverse selection (which tends to do the opposite). The net effect balances out these opposing forces.

Part 3 of Proposition 2 and Part 2 of Proposition 3 together lead to the following proposition, again stated without proof.

Proposition 4 *As the mass of market makers increases without bound, reversals in asset returns disappear, but liquidity costs tend to a strictly positive lower bound.*

The risk-bearing capacity of the market expands unboundedly as the mass of market makers goes to infinity, making reversals disappear. However, because of adverse selection caused by informed traders, liquidity costs do not become infinitesimally small even when the mass of market makers becomes unboundedly large.

2.5 Entry of Market Makers

Up to now, the number of active investors has been exogenous. We now relax this assumption and allow market makers to freely enter the market.

We begin by stating the following lemma, which is a standard result on multivariate normal random variables (see, for example, Brown and Jennings, 1989).

Lemma 1 *Let $Q(\chi)$ be a quadratic function of the random vector χ: $Q(\chi) = C + B'\chi - \chi' A\chi$, where $\chi \sim N(\mu, \Sigma)$, and A is a square, symmetric matrix whose dimension is the same as that of χ. We then have*

$$E[\exp(Q(\chi))] = |\Sigma|^{-\frac{1}{2}}|2A + \Sigma^{-1}|^{-\frac{1}{2}} \times$$

$$\exp\left(C + B'\mu + \mu' A\mu + \frac{1}{2}(B' - 2\mu' A')(2A + \Sigma^{-1})^{-1}(B - 2A\mu)\right). \tag{9}$$

The ex ante utility of the agents is derived by an application of Lemma 1. Define $\lambda = [\theta \ \epsilon \ z_1 \ z_2]$ and let Σ denote the variance matrix for this vector. Then, we can construct the square, symmetric matrix A such that $RW = \lambda' A \lambda$, where W is the wealth of the agent. Noting that the ex ante expected utility is given by $EU = E[-\exp(-RW)]$, we can apply Lemma 1 with $\mu = 0$, $C = 0$, and $B = 0$. The agent's ex ante utility thus becomes

$$EU = E[-\exp(-\lambda A \lambda')] = -|\Sigma|^{-\frac{1}{2}}|2A + \Sigma^{-1}|^{-\frac{1}{2}} = -|2A\Sigma + I|^{-\frac{1}{2}}. \tag{10}$$

We denote the determinant $|2A\Sigma + I|$ as Det_M for market makers. Note that the expected utility is monotonically increasing in the determinant.

Note that the date 2 wealth of market makers W can be written as:

$$W = \frac{(\theta + \epsilon - P)(\mu - P)}{Rv} = \frac{(\theta + \epsilon - H_1\theta - H_2 z)(a_1\theta + a_2 z) - (H_1\theta + H_2 z)]}{Rv} \tag{11}$$

Since H_1, H_2, a_1, a_2 are all available in closed form, calculating the date 2 wealth, and consequently, the expected utility from market making is straightforward and is described in the following proposition:

Proposition 5 *The expected utility from market making is decreasing in both n and m, the total masses of market makers and informed traders.*

Up to now we have assumed that the mass of market makers is exogenous. We will now consider the possibility that uninformed passive investors can pay a cost c to monitor market conditions and become an active market maker.[6] When this is the case, the mass n of market makers satisfies the condition:

[6] We assume that passive investors have zero holdings of the risky asset (recall that the asset is in zero net supply) and do not participate in the asset market. This can be viewed as the notion that these investors are simply "unaware" of the market for the stock, as in Merton (1987) or simply do not want to monitor the stock on a daily basis. Endowing them with a fixed quantity of shares makes the algebra more complicated, but the results are similar.

$$-E[\exp(-RW + Rc)] = -1, \tag{12}$$

since the utility from not entering is $-\exp(-0) = -1$. From Proposition 5 and (12), n is decreasing in c. Thus, Part 2 of Proposition 2 immediately yields the following proposition, stated without proof:

Proposition 6 *A decrease in the cost of market making reduces the magnitude of reversals in asset returns.*

The above proposition suggests that changes in technology and regulations that make it less costly for investors to actively monitor market prices and trade will reduce the magnitude of return reversals. The observed decline in return reversals in more recent times is thus consistent with this proposition.

It should also be noted that a change in the number of informed investors, m, can influence price patterns very differently when the number of market makers endogenously respond to these changes. As we showed in Proposition 2, an exogenous change in m alters the serial correlation in price changes, if we assume that the number of market makers n is held constant. However, when market makers can enter (and exit) the market, the number of market makers more than offsets the change in informed agents. Specifically, tedious but straightforward calculations lead to the following proposition:

Proposition 7 *With endogenous entry of market makers, the magnitude of the serial correlation is increasing in the total mass of informed agents, m.*

Essentially, all else held constant, an increase in the mass of informed agents decreases reversals. However, the expected change in reversals leads to a decrease in the number of market makers, which, in turn, increases reversals. The latter effect dominates the former because of the effect of the number of informed investors on the risk borne by the market makers. Our numerical simulations, however, indicate that the magnitude of the net effect is quite small. In general, across a wide range of parameter values, a proportional change in m of 10% results in a proportional change of less than 1% in the serial correlation. In other words, we do not expect a change in informed investors to have a material effect on the magnitude of return reversals when their effect can be offset by the entry of uninformed market makers.

2.6 The Case Where the Mass of Informed Traders is Uncertain

The discussion in the last subsection assumes that uninformed agents decide on whether or not to become market makers after observing the number of informed investors. We now consider a scenario where market makers make their entry decision prior to observing the mass of informed traders. As a result, shocks to the number of informed traders are not immediately offset by changes in the number of market makers.

Unfortunately, the equilibrium in this more complicated setting cannot be solved in closed form. However, the model can be solved numerically. To do this we first calculate the utility for each market maker for each m and n pair. We then calculate their expected utility for each n by integrating over all possible realizations of m. The equilibrium number of market makers is given by the value of n for which the expected utility from market making equals the expected utility from remaining a passive investor. Given this value of n we then determine properties of the price process for various realizations of m. In particular, our simulations reveal the following Proposition:

Proposition 8 *There exist parameters under which an unexpected decline in the* *number of informed investors results in a temporary increase in the magnitude of the return reversals.*

To illustrate this result, consider the parameter values $v_\theta = v_\epsilon = v_z = R = 1$, and $c = 0.005$. Suppose the mass of informed agents is uniformly distributed over the interval $[0, 1]$. We simulate the system by one million draws of the random vector $[\theta, \epsilon, z, m]$ for each integer value of n ranging from 1 to 1000. We find that the equilibrium number of market makers, i.e., the value of n that equates the average utility from market making equal to the cost of acquiring information, is 20. The regression coefficient of $F - P$ on P equals -0.117 and the serial correlation of price changes equals -0.046. Compare this to a scenario where the number of market makers equals 20, but the realized mass of informed agents drops to 0.03. In this case, the regression coefficient is -0.777 and the serial correlation is -0.071.

2.7 Discussion and Empirical Implications

To summarize, the model presented in this section extends Grossman and Stiglitz (1980) in a way that allows us to consider how the choices of different types of investors contribute to market liquidity and affect the serial correlation of individual stock returns. We find that when we allow market makers to enter and exit, a decrease in the cost of market making lowers both market impact and the magnitude of return reversals. In addition, the model suggests that in a setting where market makers enter based on the expected number of informed traders, return reversals will be temporarily stronger following an unexpected decline in the number of informed investors. In the next section, we test these implications.

3 Empirical Results

The focus of the rest of the paper is on empirically investigating the suggested implications of the model in Section 2. Specifically, we examine the change in the magnitude of return reversals that arises from changes in the number of informed investors, and we pay particular attention to the effect of innovations that occurred after 2000 that may have reduced the costs associated with market making.

3.1 Data and Methodology

Our sample consists of all NYSE/AMEX/Nasdaq common stocks with share code 10 or 11, obtained from the Center for Research in Security Prices (CRSP). The full sample period starts in January 1980 and ends in December 2011. Our sample begins in 1980 as some of the firm specific variables we consider are only available from the 1980s. In order to minimize microstructure biases emanating from low priced stocks, we exclude "penny" (low-priced) stocks whose prices are below \$5 at the end of each month. Our primary methodology involves sorting into quintiles based on stock returns in month t and evaluating the future returns in month $t + 1$. We implement the conventional contrarian strategy by taking long positions in the bottom quintile of stocks (loser portfolio) in the past month and shorting the stocks in the top quintile (winner portfolio). The zero-investment contrarian profit (Jegadeesh, 1990) is computed as the loser minus winner portfolio returns in month $t + 1$.

The contrarian profits represent the returns to supplying liquidity (Stoll, 1978; Grossman and Miller, 1988; Nagel, 2012; and others). More recently, Hameed and Mian (2013) show that the monthly price reversal, and, in turn, the return to providing liquidity, is better identified using industry-adjusted returns. For example, they show that the industry-adjusted stock returns reduce the noise emanating from price reactions to public information and increase the signal coming from order imbalances (or liquidity demand). Specifically, they use deviation of monthly stock returns from the average return on the corresponding industry portfolio to sort stocks into winner and loser portfolios. Thus, as an alternative approach, we construct industry-adjusted contrarian portfolios by sorting stocks into loser and winner quintiles based on the industry-adjusted stock returns. Similar to Hameed and Mian (2013), we rely on the Fama and French (1997) system of classifying firms into 48 industries based on the four-digit SIC codes.

The U.S. equity market has undergone tremendous structural changes in the past decade which have eroded the barriers to entry in the business of supplying liquidity. These structural changes (see, e.g., Chordia, Roll, and Subrahmanyam (2011) and Chordia, Subrahmanyam and Tong (2013)) include the introduction of decimalization, greater participation of hedge funds and other informed institutional investors, and a sharp increase in high frequency traders who have largely replaced the traditional liquidity providers such as NYSE specialists and Nasdaq market makers. To examine the impact of these changes on the return reversals, we split our sample into two sub-periods: 1980–1999 and 2000–2011. We expect the increase in the competition for liquidity provision to have a negative impact on contrarian profits.

We report the contrarian portfolio returns in month $t + 1$ for all stocks as well as stocks sorted into size groups. The analysis across size groups is motivated by recent findings in Fama and French (2008), who show that equal-weighted long-short portfolios may be dominated by stocks that are plentiful but tiny in size. On the other hand, value-weighted portfolios are dominated by a few large firms, and hence, the resulting portfolio returns is not representative of the profitability of the strategy. Thus, following Fama and French (2008), we group stocks into three categories based on the beginning of period market capitalization: microcaps (defined as stocks with size less than the 20th NYSE size percentile); small firms (stocks that are between the 20th and 50th NYSE size percentiles) and big firms (stocks that are above the 50th NYSE size percentile).

In addition to the equal-weighted raw contrarian portfolio returns for each category of stocks, we report alphas from a four-factor model that consists of the three Fama and French (1993) factors: the market factor (excess return on the value-weighted CRSP market index over the one month T-bill rate), the size factor (small minus big firm return premium, SMB), the book-to-market factor (high book-to-market minus low book-to-market return premium, HML), as well as the Pástor and Stambaugh (2003) liquidity factor. The standard errors in all the estimations are corrected for autocorrelation with three lags using the Newey and West (1987) method.

3.2 Unconditional Short-Term Reversals

Table 1 contains the returns to the monthly contrarian investment portfolios. In Panel A, we report the returns to the contrarian portfolio strategy formed using unadjusted stock returns. Over the 1980–2011 sample period, the (equal-weighted) average contrarian return across all stocks is a significant 0.54 percent per month (t-statistic=2.86). We also obtain similar raw profits in each of the three groups of microcaps, small, and big firms. The profits weaken considerably after adjusting for risk exposures using the four-factor model and become insignificant, except for microcaps.

Consistent with Hameed and Mian (2013), the profit figures in Panel B of Table 1 are larger in each category when the portfolios are formed using industry-adjusted returns. For instance, the contrarian profit for all firms increases to 1.02 percent (t-statistic=7.27), with a risk-adjusted return of 0.84 percent (t-statistic=5.93). The industry-adjusted contrarian profits are significant in each of the size groups for the full sample period, with risk-adjusted returns ranging from 0.46 percent (big firms) to 1.04 percent (microcaps).

When we split the sample into the pre and post 2000 time periods, we observe a significant decline in the contrarian profits in the recent decade, particularly for the small and big firms. The conventional contrarian profits for small and big firms are significant only in the 1980–1999 sub-period, and lose their significance when we adjust for exposure to common risk factors. For the small firms, the industry-based contrarian profit is lower in the later sub-period, but survives the adjustment for risk. The change in the magnitude of the reversals in the recent decade is strongest for the large firms. The industry-adjusted contrarian profit for large firms drops from 0.82 percent (t-statistic=4.61) in 1980–1999, to an insignificant 0.12 percent (t-statistic=0.39) after 2000. On the other hand, we do not observe a drop in the contrarian profits over similar periods when applied to the microcaps. In fact, the contrarian profits for microcaps increase slightly from 1.03 percent in 1980–1999 to 1.14 percent in 2000–2011. These results illustrate that the erosion of barriers to entry in the liquidity provision business (Hendershott, Jones, and Menkveld (2011)) has had a dramatic effect on the magnitude of return reversals, particularly for small and large stocks.

3.3 Institutional Exits and Return Reversals

Our model predicts that the magnitude of reversals is affected by the presence of informed investors. *Ceteris paribus*, an increase (decrease) in the number of informed investors following a stock decreases (increases) the magnitude of the stock's return reversals.

For our initial test of this proposition, we examine changes in the number of institutions holding each stock, using data from Thomson-Reuters Institutional Holdings

(13F) database.[7] We break down the institutional investors into informed and uninformed types following Abarbanell, Bushee and Raedy (2003), where the informed institutions are defined as investment companies and independent investment advisors. The idea here is that such institutions are more likely to be active investors. Other institutions, such as bank trusts, insurance companies, corporate/private pension funds, public pension funds, university and foundation endowments, have longer investment horizons and trade less actively.[8] We compute the number of informed institutional investors owning shares in a firm at the end of each quarter, labeled as (*Informed_NumInst*) and denote a change in the number of informed institutional investors over the quarter as Δ*Informed_NumInst*.

To estimate the relation between institutional holdings and return reversals we examine the return patterns for two groups of stocks: those that experienced a decline in informed investor holdings over the quarter prior to month $t-1$, and those that did not. As shown in Table 2, return reversals are stronger following the exit of active institutions. For the full sample period and across all stocks, the risk-adjusted contrarian strategy yields a significant 0.55 percent per month when there is a decline in informed institutions, while the returns are insignificant at 0.14 percent for firms that had an increase in informed institutional investors. We obtain qualitatively similar results when institutional exits are measured by a drop in the percentage of shares held by active investors.

Table 2 also presents the contrarian profits for the two sub-periods: 1980–1999 and 2000–2011. In the sample including all firms, we find that exits by informed investors are followed by greater return reversals in both sub-periods. However, the

[7]The institutional ownership data comes from quarterly 13F filings of money managers to the U.S. Securities and Exchange (SEC). The database contains the positions of all the institutional investment managers with more than $100 million U.S. dollars under discretionary management. All holdings worth more than $200,000 U.S. dollars or 10,000 shares are reported in the database.

[8]We thank Brian Bushee for making the institutional investor classification data available at this website: http://acct3.wharton.upenn.edu/faculty/bushee/IIclass.html.

effect is relatively weak in the second sub-period. Table 2 also reports the breakdown of the results for each of the three size groups. We find that declines in the number of informed investors accentuate the reversals significantly in the earlier sub-period for each of the three size-based groups. For example, the risk-adjusted contrarian profits for large firms is 0.53 percent (t-statistic=2.28) for the sample with a decline in informed investors, which is significantly higher than the profit of 0.06 percent for large firms that experience an increase in informed investors. In contrast, in the recent decade, we observe a relation between changes in the number of informed investors and return reversals only in the sample of microcaps.[9]

3.4 Stock Returns and Changes in Institutional Ownership

As we just discussed, our findings in Table 2 are consistent with the predicted relation between changes in informed investors and return reversals (especially in the earlier sub-period). However, using changes in the number of active institutional investors holding a stock as a proxy for active informed investors has several drawbacks. First, institutional holdings are measured only at a quarterly frequency. As a result, the time lag between the observed changes in institutional holdings and the returns of the reversal strategy can be up to three months. Second, rather than the number of active traders that follow the stock, which is the variable suggested by our model, we are measuring the number of institutions that hold the stock, which can be subject to endogeneity problems that can bias our inferences. For example, active institutions may steer away from stocks that are expected to become less liquid. Third, an increase in reversals in our model comes from unanticipated changes in the number of informed investors; however, the change in institutional investors we observe can be partially anticipated.

[9] Our results are also consistent with recent findings in Anand, Irvine, Puckett and Venkataraman (2013) who report that liquidity-supplying institutional investors decreased trading in riskier (small) stocks (i.e. withdraw liquidity supply) during the recent financial crisis period.

To address these issues we use past stock returns (over the previous three months) as an instrument for unanticipated changes in the number of investors who actively participate in a stock. Stock returns, by their nature, are largely unanticipated, and we conjecture that stocks receive less attention from active institutions when their market capitalizations drop. There may be direct reasons why this may be the case as smaller stocks are less liquid, and there may be window dressing reasons (they do not want to be associated with losers).[10]

To document the relation between stock returns and institutional ownership, we first sort stocks into quintiles based on the cumulative three-month stock returns from month $t-3$ to $t-1$ (*3M*). For the stocks in each of these quintiles, we compute the level and changes in the number of institutional investors, separately reporting the figures for those classified as informed institutional investors as well as those classified as uninformed. In addition, we present the corresponding figures for the percentage of institutional share ownership. In each case, we report the level (in month $t-1$) and changes in these measures over the months $t-3$ to $t-1$ based on the latest information during the quarter.

Panel A of Table 3 shows that the number (and percentage) of informed investors in month $t-1$ is lower for *3M* losers than for *3M* winners. Further, the difference in ownership levels of uninformed (less active) investors is not significantly related to the contemporaneous stock performance. Panel B shows that informed institutional participation declines for *3M* loser stocks. Indeed, there is a monotonic increase

[10] There is some degree of circularity in these arguments. Stocks become less liquid because they are expected to be less liquid. Indeed, Spiegel and Subrahmanyam (1995) present a model where contemporaneous liquidity reflects anticipated future illiquidity caused by anticipated shocks to aggregate endowments, which, in turn, depend on the mass of participating investors. There also is a literature on herding, (e.g., Hirshleifer, Subrahmanyam and Titman (HST) (1994)) that addresses this circularity. Within the context of HST's fully rational model, there are situations where investors optimally choose to coordinate their choices of which stocks to evaluate. Within this setting it is very natural to have fewer active investors following stocks that show reductions in market capitalization.

in Δ*Informed_NumInst* as we move from losers to winners. On average, there is a decline (increase) of 1.7 (4.2) informed investors for *3M* losers (winners), representing a 4 (10) percent drop (increase) from the beginning of quarter *Informed_NumInst*. On the other hand, changes in the uninformed institutions are less sensitive to stock performance. The decline (increase) in the number of uninformed institutions for past *3M* losers (winners) is smaller at 1 (6) percent. We reach a similar conclusion when we compare the changes in percentage of institutional ownership across *3M* losers and winners for the informed and uninformed institutional investors. Hence, the numbers in Panel B of Table 3 indicate a strong positive relation between *3M* stock returns and changes in the participation of informed institutions over the same quarter.

The remaining panels in Table 3 present the changes in institutional ownership in subsequent quarters. Interestingly, the change in institutional holdings that is associated with the previous quarter stock return is persistent. In particular, as we show in Panels C and D, we do not see the institutional holdings of the past quarter losers returning to their previous levels in the following quarters. The *3M* losers (winners) continue to experience a decrease (increase) in the number and percentage of institutions holding these stocks in the next two quarters. In unreported results, we find that the drop in institutional holdings lasts for up to four quarters. Our theoretical model suggests that even though negative past returns are associated with a long-lasting drop in institutional holdings, the impact of this drop on reversals should be temporary as market making capacity adjusts in response to the change in institutional holdings. We examine if there is empirical support for this notion in Section 3.6 of the paper.

3.5 Quarterly Returns and One-Month Return Reversals

The results in Tables 3 suggest that past stock price performance can be used as an instrument for changes in the number of active informed investors. Given this, we expect past returns to be associated with the magnitude of future return reversals.

To examine the relation between return reversals and past returns we sort stocks into twenty-five portfolios based on their return performance in the past one quarter and past one month. Specifically, in each month t, we sort stocks into quintiles based on returns over the past three months, that is, months $t-3$ to $t-1$. The stocks in the lowest quintile are labeled as *3M* losers and those in the top quintile are *3M* winners. We also independently sort all stocks into five equal groups using their returns in month t to produce *1M* losers (stocks with lowest of month t returns) and *1M* winners (stocks with highest month t returns). Based on these independent sorts, we form 25 portfolios and calculate their mean returns, which we report in Table 4.

As shown in Table 4, the monthly contrarian profits increase dramatically when we move from the *3M* winner quintile to the *3M* loser quintile. In Panel A, the equal-weighted contrarian portfolio of all stocks produces the highest reversal return of 1.68 percent per month (t-statistic=7.8) for stocks that are *3M* extreme losers. The reversal profits are virtually zero for the *3M* winner stocks and the difference between the contrarian profits generated by the *3M* loser stocks and *3M* winner stocks is highly significant (t-statistic=7.46). The economic and statistical significance is similar when we adjust for exposure to the four common risk factors.

We conduct additional tests to examine how these results relate to the market capitalizations of the stocks. Consider now the results for size groupings in Panel A of Table 4. Although the results are stronger for microcaps, we find significant reversals among the *3M* losers for small and big firms as well. In contrast, there is no evidence of contrarian profits for any of the size groups for stocks which are *3M* winners.[11]

We next examine the returns of these portfolios in the pre- and post-2000 periods. As shown in Panels B and C of Table 4, the profitability of the contrarian strategy that employs all stocks is much lower in the post-2000 period, but is highest for *3M* loser stocks in both sub-periods. For the *3M* losers, the average risk-adjusted contrarian profit is 1.84 percent in the 1980–1999 period, and declines to 1.25 percent in the recent period. The decline in return reversals is especially large for the *big* firms, which realize an average reversal profit of 1.34 percent (t-statistic=4.96) in the earlier sub-period, but only 0.49 percent (t-statistic=1.13) in the recent decade. These findings are consistent with the increased competition in market making during the recent period.[12]

Next, in Table 5, we consider the contrarian profits computed using industry-adjusted stock returns. These profits are uniformly higher than those reported in Table 4, consistent with Hameed and Mian (2013), and are decreasing in *3M* returns. The risk-adjusted profits remain economically and statistically significant within each of the three size groups, and in both sub-periods, when these stocks are also *3M* losers. Moreover, the reversal profits among *3M* loser stocks are lower in the second sub-period, across all stocks. For example, the industry-adjusted contrarian strategy applied to the big firms that are also *3M* losers yields a significant risk-adjusted monthly profit of 1.58 percent and 0.63 percent in the first and second sub-periods. On the other hand, the evidence of reversals is lacking among *3M* winners, across sub-periods and size groups.[13] Overall, the evidence supports the main proposition in our

[11]In unreported results, we find that the risk-adjusted contrarian profits primarily emanate from one-month winner stocks, across all size groups. This is consistent with provision of liquidity being more difficult for the short-leg due to shorting costs.

[12]We also find that frictions in market prices, such as bid-ask bounce, do not drive our central findings. Specifically, when we skip a week between formation and holding months in the contrarian strategy we get qualitatively similar results, in that all profit figures of Table 4 remain significant, except for largest firms in the second sub-period. Results are available upon request.

[13]Da, Liu, and Schaumburg (2013) also consider reversal profits in different subperiods on a

model that the temporary decline in active investors and market making capacity is a significant predictor of return reversals.

3.6 Longer Horizon Returns and Monthly Reversals

Our theoretical model predicts that an unanticipated reduction in the number of informed investors leads to a temporary increase in the return reversals. Specifically, when active uninformed investors can enter to offset the effect of informed investors, past returns should only have a temporary effect on the magnitude of reversals. In this sub-section, we examine whether or not this change in the magnitude of reversals is indeed temporary.

In addition to using month $t-3$ to $t-1$ returns to define *3M* winners and losers, our tests in this subsection correlate the magnitude of reversals to stock returns from the earlier quarter (i.e. months $t-6$ to $t-4$). If additional uninformed market makers enter following exits by informed institutions, we expect past *4-6M* stock performance to be less important, and potentially immaterial, in predicting monthly reversals. To analyze the effect of past *4-6M* returns, stocks are independently sorted into quintiles according to past *4-6M* and *3M*, at the end of each month t. For each of these 25 groupings, we examine the one-month reversal profits, where stocks are classified as winners and losers if they belong to top and bottom quintiles based on their returns in month t. The contrarian strategy evaluates the returns in month $t+1$ as before, and the results are presented in Table 6.

The main finding for the full-sample period (Panel A) is qualitatively similar to those in Table 4: *3M* losers exhibit greater reversals than *3M* winners, independent of the stock performance in the prior $t-4$ to $t-6$ months. The reversal profits are also higher if the stocks declined two quarters ago, indicating that past *4-6M* returns

risk-adjusted and industry-adjusted basis, but do not consider the effects of institutional exits and longer-term returns on monthly reversal profits.

incrementally predicts reversals in month $t + 1$. However, the more recent quarter has a much stronger effect on the magnitude of the reversals.

The sub-period results in Panels B and C of Table 6 reveal that the impact of past *4-6M* returns on reversals is significant in the first sub-period, but is not reliably positive in the second sub-period. Among the past *3M* losers, we find that past *4-6M* losers predict significantly higher reversal profits than past *4-6M* winners in the 1980–1999 period, consistent with high participation costs delaying the entry of market makers. On the other hand, the insignificant influence of past *4-6M* returns on reversals in the recent decade is consistent with the view that entry of market makers has become less costly. In unreported results, we considered the effect of returns in months $t - 9$ to $t - 7$ as well as months $t - 12$ to $t - 10$ and found them to be irrelevant in predicting reversals. These results indicate that even in the earlier period past returns have only a temporary effect on the magnitude of return reversals.

3.7 Extreme Losers and Other Illiquidity Measures

While we have emphasized the effect of unanticipated changes in informed investor activity on return reversals, our model also has implications for illiquidity, since entry and exit by informed investors and market makers affect illiquidity. In this section we consider how the past *3M* returns relate to the Amihud (2002) measure, which is an empirical proxy for illiquidity. Thus, we define a measure $ILLIQ$ for each stock as

$$ILLIQ_{i,t} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} \times 10^6,$$

where R_{itd} is the return for stock i, on day d of month t, $DVOL_{itd}$ is the dollar trading volume of stock i, on day d of month t, and D_{it} represents the number of trading days for stock i in month t.[14]

[14]To account for differences in the reported trading volume for stocks traded on NYSE/AMEX and Nasdaq, we adjust Nasdaq volume following the procedure outlined in Gao and Ritter (2010). Specifically, Nasdaq volume is scaled to account for the (declining) effect of reported trades among market makers.

Consistent with our model, we find there is an inverse relation between the Amihud measure and past stock returns. Specifically, the *3M* losers have the highest Amihud measure, and *ILLIQ* monotonically decreases for stocks that have performed increasingly better in the past three months. Moreover, the *3M* losers experience an increase in illiquidity while the *3M* winners show a large decrease in illiquidity, as captured by the Amihud measure.[15]

Given the link between past returns and our illiquidity proxy, it is important to also consider how illiquidity directly influences the relation between past returns and reversal magnitudes. As our model suggests, and as Avramov, Chordia and Goyal (2006) show, short-term contrarian profits are strongly related to stock illiquidity.

To examine the interrelations between past returns, the Amihud measure of illiquidity, and the magnitude of reversals, we independently sort stocks into quintiles along two dimensions: their past three-month returns (months $t-3$ to $t-1$) and their average Amihud measures over the same three months. We match these 25 groups of stocks with stocks sorted by the one month return in month t to generate contrarian profits in the holding month $t+1$.

The contrarian profits for these 25 groups of stocks are presented in Panel A of Table 7. As can be seen, the magnitude of both return reversals and liquidity decrease with past performance. While stocks with higher levels of the Amihud measure earn higher contrarian returns, we find that past returns play a significant role in predicting reversals. We find significant risk-adjusted contrarian profits in all liquidity groups except the most liquid quintile, if the stocks are *3M* losers. For example, for the full sample period, we obtain the highest monthly risk-adjusted profit of 2.43 percent (t-statistic=7.57) for stocks that are both *3M* losers and are

[15] The average Amihud measure in month $t-1$ for the extreme losers over months $t-3$ to $t-1$ is 63% higher than that for the extreme quintile of winners over the same period. We also find that the *3M* losers (winners) experience an increase (decrease) in the illiquidity measure of 31.3% (31.2%) in month $t-1$ relative to month $t-3$.

most illiquid. The corresponding profits for *3M* loser stocks which are relatively liquid (middle three quintiles) remain significant at above 1.3 percent per month. On the other hand, there are no reversal profits for stocks which are *3M* winners, including the stocks which belong to the most illiquid quintile. Moreover, the difference in risk-adjusted contrarian profits between *3M* losers and *3M* winners is significant within all liquidity quintiles, including the most liquid stocks.

The above evidence, that three-month stock performance contains information about return reversals that is not subsumed by cross-sectional differences in the Amihud (2002) liquidity measure, suggests that past price performance, and the concomitant institutional exits, reflect facets of illiquidity not captured by the Amihud measure. This would not be surprising, given that it is likely that the Amihud measure is a noisy estimate of liquidity. In unreported analysis, we find that the effect of past three month returns is also not subsumed by past turnover, which captures other aspects of liquidity. In addition, we look directly at shocks to liquidity, using the measure recently introduced in Bali, Peng, Shen, and Tang (2013).[16] In unreported regressions we find that these liquidity shocks are in fact related to the magnitude of reversals. In particular, we find that stocks that experience a large illiquidity shock in the formation month exhibit greater reversals, consistent with the expectation that reversals are related to temporary non-informational shocks. However, the *3M* loser effect identified in our analysis holds for each of the liquidity shock quintiles.[17] Finally, we find that the results we present in Table 7 holds within sub-periods, similar to our findings in earlier subsections.

[16] Specifically, the illiquidity shock for stock i in formation month t is defined as the difference between $ILLIQ_{it}$ and the average *ILLIQ* over the previous twelve months from $t-12$ to $t-1$, scaled by its standard deviation over the previous twelve months.

[17] The increase in reversals is strongest among the stocks with low liquidity shocks: the risk-adjusted contrarian profits increase from an insignificant -0.12 percent for *3M* winners to 2.24 percent for the *3M* losers. The differences in profits between *3M* losers and *3M* winners ranges from 1.13 percent to 2.37 percent per month and is significant in each of the liquidity shock groups.

3.8 Extreme Losers and Volatility

Stocks that experience extreme negative returns are also likely to be more volatile in the future, as described in Glosten, Jagannathan, and Runkle (1993). Further, Huang, Liu, Rhee and Zhang (2010) argue that monthly reversals are related to stock volatility. Our theoretical model is also consistent with greater volatility being associated with lower liquidity, and hence, higher reversals. Further, if past *3M* losers are more volatile, this might magnify the return differential, and, in turn, the contrarian profits, across winners and losers. Hence, it is important to investigate the extent to which the volatility differences among *3M* losers and winners contribute to the reversals.

To evaluate how volatility differences contribute to our results, we compute stock return volatility for each stock as the standard deviation of daily returns over months $t-3$ to $t-1$. Stocks are then (independently) double sorted into quintiles by their volatility and *3M* returns to produce 25 groups. We then compute the contrarian profits within each of the 25 groups and report the mean profits in Panel B of Table 7.

Consistent with the earlier literature, we find that more volatile stocks exhibit greater reversals. However, the positive association between volatility and reversals is confined to the extreme *3M* losers. Also, within each volatility quintile, the *3M* loser stocks exhibit the greatest reversals and significantly so, except for the stocks in the lowest volatility quintile. On the other hand, there is little evidence of reversals among the *3M* winners, even amongst those stocks that belong to the high volatility group. The evidence that emerges from Panel B is that the *3M* loser effect on reversals is robust to controlling for volatility. Specifically, volatility increases reversals, but does not materially affect the robust conclusion that contrarian profits are predominant only in three-month losers.

4 Conclusion

Ever since Jegadeesh (1990), financial economists have debated the underlying cause of monthly return reversals. On one hand, the evidence is consistent with microstructure models that consider the risks and frictions associated with the provision of liquidity. On the other hand, the evidence is consistent with behavioral stories which include investors that overreact to short-term information.

Our model is in the tradition of the rational microstructure models, which we extend to allow for exogenous changes in the number of informed investors and the endogenous entry of uninformed but active investors who act as market makers. Our model embeds reversals, and shows that this phenomenon is particularly pronounced when market making capacity slowly adjusts to an unanticipated drop in the mass of informed investors. For the most part, the empirical evidence is consistent with the model. In particular, we find that large declines in stock prices, lead to a decline in institutional investor participation, and to a material (but temporary) increases in reversals-based profits.

There are, of course, behavioral stories that can also explain the observed relation between past stock returns and the magnitude of return reversals. Specifically, there may be a tendency to overreact to the information implicit in the order flow of past losers. For example, losing stocks may attract more attention, so that investors may attach more significance to the large institutional buys and sells of past losers than they really should. Although we do not explore this possibility in this paper, this behavioral explanation may warrant exploration in future work.

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Appendix A: Proofs

Proof of Proposition 1: As part of their optimization, the uninformed agents solve a filtration problem which infers θ from the price P, which is a linear combination of θ and z. Let

$$\tau \equiv \frac{m\theta}{Rv_\epsilon} + z.$$

Since μ and v are non-stochastic from the uninformed's perspective, P is observationally equivalent to τ. Thus, we have

$$\mu = E(\theta|\tau) = \frac{Rmv_\theta v_\epsilon}{m^2 v_\theta + R^2 v_\epsilon^2 v_z}\tau, \tag{13}$$

and

$$v = v_\epsilon + v_\theta - \frac{m^2 v_\theta^2}{m^2 v_\theta + R^2 v_\epsilon^2 v_z}. \tag{14}$$

Note that μ can be written as

$$\mu = a_1\theta + a_2 z \tag{15}$$

where

$$a_1 = \frac{m^2 v_\theta}{m^2 v_\theta + R^2 v_\epsilon^2 v_z} \tag{16}$$

and

$$a_2 = \frac{Rmv_\theta v_\epsilon}{m^2 v_\theta + R^2 v_\epsilon^2 v_z}. \tag{17}$$

Solving for P from (3), and substituting for μ and v from (13) and (14), respectively, we have the expressions in Proposition 5. $\|$

Proof of Proposition 2: For Part 1, note that

$$\text{cov}(F - P, P) = v_\theta H_1(1 - H_1) - H_2^2 v_z. \tag{18}$$

Substituting for H_1 and H_2 into the right-hand side of (18) from (6) and (7), respectively, we obtain (8). Further,

$$\rho^2 = \frac{A_1}{A_2} \tag{19}$$

where

$$A_1 \equiv R^2 v_\epsilon^2 v_z [m^2 v_\theta + R^2 v_\epsilon v_z (v_\epsilon + v_\theta)]^2,$$

and

$$\begin{aligned} A_2 &= (m^2 v_\theta + R^2 v_\epsilon^2 v_z)[(m^4 v_\theta^2 + 2m^3 n v_\theta^2 + m^2 v_\theta (n^2 v_\theta + 2R^2 v_\epsilon v_z (v_\epsilon + v_\theta)) \\ &+ 2mnR^2 v_\epsilon v_\theta v_z (v_\epsilon + v_\theta) + R^2 v_\epsilon^2 v_z (n^2 v_\theta + R^2 v_z (v_\epsilon + v_\theta)^2)]. \end{aligned}$$

It is easy to verify that the derivatives of A_1/A_2 with respect to m and n are both negative. Part 3 of the proposition follows from taking the relevant limits on the right-hand side of (19). $\|$

Proof of Proposition 5: Substituting for H_1, H_2, a_1, and a_2 in (11), and calculating the determinant, we find that Det_M is given by $[\sum_{i=0}^{9} \beta_i m_i]/C$, where $\beta_9 = v_\theta^3$, $\beta_8 = 3nv_\theta^3$,

$$\beta_7 = 3v_\theta^2 [n^2 v_\theta + R^2 v_\epsilon v_z (v_\epsilon + v_\theta)]$$

$$\beta_6 = nv_\theta^2 [n^2 v_\theta + 3R^2 v_\epsilon v_z (3v_\epsilon + 2v_\theta)]$$

$$\beta_5 = R^2 v_\epsilon v_\theta v_z (3n^2 v_\theta (3v_\epsilon + v_\theta) + R^2 v_\epsilon v_z (3v_\epsilon^2 + 7v_\epsilon v_\theta + 3v_\theta^2))$$

$$\beta_4 = nR^2 v_\epsilon^2 v_\theta v_z (3n^2 v_\theta + R^2 v_z (9v_\epsilon^2 + 13 v_\epsilon v_\theta + 3v_\theta^2))$$

$$\beta_3 = R^4 v_\epsilon^3 v_z^2 (3n^2 v_\theta (3v_\epsilon + 2v_\theta) + R^2 v_z (v_\epsilon^3 + 7v_\epsilon^2 v_\theta + 5v_\epsilon v_\theta^2 + v_\theta^3))$$

$$\beta_2 = nR^4 v_\epsilon^4 v_z^2 (3n^2 v_\theta + R^2 v_z (3v_\epsilon^2 + R^2 v_z (3v_\epsilon^2 + 10 v_\epsilon v_\theta + 4v_\theta^2))$$

$$\beta_1 = R^6 v_\epsilon^5 v_z^3 (3n^2 (v_\epsilon + v_\theta) + R^2 v_z (3v_\epsilon^2 + 2v_\epsilon v_\theta + v_\theta^2))$$

$$\beta_0 = nR^6 v_\epsilon^6 v_z^3 (n^2 + R^2 v_z (3v_\epsilon + v_\theta)),$$

and

$$C = [m^3 v_\theta + m^2 n v_\theta + mR^2 v_\epsilon v_z (v_\epsilon + v_\theta) + nR^2 v_\epsilon^2 v_z]^3$$

The derivative of the above determinant with respect to n is given by

$$-F_1/G$$

where

$$F_1 \equiv 2R^4 v_\epsilon^3 v_z^2 (m^2 v_\theta + R^2 v_\epsilon^2 v_z)(m^5 v_\theta^2 + m^4 n v_\theta^2 + 2m^3 R^2 v_\epsilon v_\theta v_z (2v_\epsilon + v_\theta)$$
$$+ \quad m^2 n R^2 v_\epsilon v_\theta v_z (4v_\epsilon + v_\theta) + m R^4 v_\epsilon^2 v_z^2 (3v_\epsilon^2 + v_\epsilon v_\theta + v_\theta^2) + n R^4 v_\epsilon^3 v_z^2 (3v_\epsilon + v_\theta))$$

and

$$G \equiv [m^3 v_\theta + m^2 n v_\theta + m R^2 v_\epsilon v_z (v_\epsilon + v_\theta) + n R^2 v_\epsilon^2 v_z]^4,$$

which is negative.

Similarly, the derivative of the determinant with respect to m is given by

$$-F_2/G,$$

where $F_2 = \sum_{i=0}^{7} \gamma_i m^i$, with $\beta_7 = 4R^4 v_\epsilon^3 v_\theta^3 v_z^2$, $\beta_6 = 6nR^4 v_\epsilon^3 v_\theta^3 v_z^2$,

$$\beta_5 = 2R^4 v_\epsilon^3 v_\theta^2 v_z^2 (n^2 v_\theta + R^2 v_\epsilon v_z (11v_\epsilon + 5v_\theta)),$$

$$\beta_4 = 2nR^6 v_\epsilon^4 v_\theta^2 v_z^3 (17v_\epsilon + 6v_\theta),$$

$$\beta_3 = 4R^6 v_\epsilon^4 v_\theta v_z^3 (n^2 v_\theta (3v_\epsilon + v_\theta) + 2R^2 v_\epsilon v_z (3v_\epsilon^2 + 2v_\epsilon v_\theta + v_\theta^2)),$$

$$\beta_2 = 2nR^8 v_\epsilon^5 v_\theta v_z^4 (17v_\epsilon^2 + 9v_\epsilon v_t heta + 3v_\theta^2),$$

$$\beta_1 = 2R^8 v_\epsilon^6 v_z^4 (n^2 v_\theta (5v_\epsilon + 2v_\theta) + R^2 v_z (v_\epsilon + v_\theta)(3v_\epsilon^2 + 2v_\epsilon v_\theta + v_\theta^2)),$$

and

$$\beta_0 = 2nR^{10} v_\epsilon^7 v_z^5 (3v_\epsilon^2 + 5v_\epsilon v_\theta + v_\theta^2,$$

which is also negative. $\|$

Proof of Proposition 7: We have that

$$\frac{d\rho^2}{dm} = \frac{\partial \rho^2}{\partial m} \frac{dn}{dm} + \frac{\partial \rho^2}{\partial m}. \tag{20}$$

The partial derivatives above are easily obtained from (19). From the implicit function theorem,

$$\frac{dn}{dm} = -\frac{dDet_M/dm}{dDet_M/dn}$$

where the expression for Det_M is provided in the proof of Proposition 5. Substituting for the various derivatives in (20) it is verified through tedious algebra that $d\rho^2/dm$ is positive. Specifically, the numerator and denominator of the derivative are respectively 14th and 17th order polynomials in m, with coefficients that are all positive. Detailed expressions are available upon request.$\|$

Appendix B: Variable Definitions

- *ILLIQ*: The Amihud illiquidity measure in a given month t is computed as follows:
$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} \times 10^6,$$
where R_{itd} is the return for stock i, on day d of month t, $DVOL_{itd}$ is the dollar trading volume of stock i, on day d of month t, and D_{it} represents the number of trading days for stock i in month t. In addition, Nasdaq trading volume is adjusted following Gao and Ritter (2010). Prior to February 1, 2001, we divide Nasdaq volume by 2. From February 1, 2001 to December 31, 2001, we divide Nasdaq volume by 1.8. For the years 2002 and 2003, we divide Nasdaq volume by 1.6. No adjustment is made from 2004 onwards.

- *NumInst*: The number of institutional investors that hold a stock in each quarter.

- *Informed_NumInst*: The number of informed institutional investors that hold a stock in each quarter. Institutions are classified into five types (obtained from Brian Bushee's website: http://acct3.wharton.upenn.edu/faculty/bushee/ IIclass.html): bank trust, insurance company, investment company, independent investment advisor and others (corporate/private pension fund, public pension fund, university and foundation endowments, miscellaneous). We merge the investment company and independent investment advisor into the informed institution group.

- *IO*: Institutional ownership in a given quarter q is computed as follows:
$$IO_{i,q} = \sum_f SHR_{i,f,q}/SHROUT_{i,q},$$
where $SHR_{i,f,q}$ refers to the number of shares of stock i held by fund f in quarter q, and $SHROUT_{i,q}$ refers to the shares outstanding at the same time.

- *Informed_IO*: The ownership held by informed institutional investors in each quarter. The classification of informed institution is the same as in *Informed_NumInst*.

Table 1: Returns to Contrarian Investment Strategies

Panel A presents returns to the conventional contrarian strategy. At the end of each month t, stocks are sorted into three size groups ─ microcaps, small stocks and big stocks. The breakpoints are the 20th and 50th percentiles of the market capitalization for NYSE stocks at the beginning of month t. Within each size group, stocks are further sorted into quintiles according to their month t returns. The Loser (Winner) portfolio comprises of the bottom (top) quintile of stocks. Panel A reports, for each size group (Micro, Small and Big) and All firms, the equal-weighted return in month $t+1$ for the contrarian strategy of going long (short) the Loser (Winner) stocks. The profits are reported for the full sample (1980 ─ 2011) as well as two sub-periods: 1980 ─ 1999 and 2000 ─ 2011. Risk-adjusted returns are based on a four-factor model comprising the three Fama-French factors (market, size and book-to-market) and the Pástor-Stambaugh liquidity factor. Panel B reports similar statistics using an industry-adjusted contrarian strategy, where the Loser/Winner stocks are sorted into quintiles according to their month t industry-adjusted returns, and industries are defined by the Fama-French 48 industry classification based on four-digit SIC codes. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Returns to Contrarian Investment Strategies								
	Returns				Four-Factor adjusted Returns			
	Firm Size				Firm Size			
Sample Period	Micro	Small	Big	All	Micro	Small	Big	All
1980 ─ 2011	0.626***	0.556**	0.374*	0.541***	0.434**	0.272	0.090	0.308
	(3.32)	(2.40)	(1.69)	(2.86)	(2.25)	(1.12)	(0.39)	(1.57)
1980 ─ 1999	0.557***	0.593**	0.530**	0.546***	0.440**	0.369	0.368	0.403**
	(2.81)	(2.55)	(2.52)	(2.88)	(2.12)	(1.47)	(1.52)	(2.00)
2000 ─ 2011	0.741**	0.495	0.115	0.532	0.635**	0.401	0.026	0.479
	(2.17)	(1.07)	(0.25)	(1.43)	(2.00)	(0.96)	(0.06)	(1.38)

Panel B: Returns to Industry-Adjusted Contrarian Investment Strategies								
	Returns				Four-Factor adjusted Returns			
	Firm Size				Firm Size			
Sample Period	Micro	Small	Big	All	Micro	Small	Big	All
1980 ─ 2011	1.191***	1.026***	0.660***	1.023***	1.036***	0.793***	0.456***	0.838***
	(7.79)	(5.77)	(4.12)	(7.27)	(6.79)	(4.59)	(2.85)	(5.93)
1980 ─ 1999	1.146***	1.175***	0.984***	1.110***	1.030***	0.956***	0.815***	0.955***
	(6.62)	(6.20)	(6.14)	(7.31)	(5.88)	(5.00)	(4.61)	(6.21)
2000 ─ 2011	1.267***	0.779**	0.120	0.879***	1.135***	0.671**	0.123	0.816***
	(4.56)	(2.21)	(0.38)	(3.18)	(4.05)	(2.00)	(0.39)	(2.79)

Table 2: Returns to Contrarian Investment Strategies: Change in Informed Investors

Stocks are sorted into three size groups — microcaps, small stocks and big stocks, using NYSE 20th and 50th percentiles as breakpoints. Within each size group, stocks are independently sorted into 2×5 portfolios according to whether there is a decrease or increase in the number of informed institutions over the past three months, $t-3$ to $t-1$, (ΔInformed_NumInst) and one-month stock returns (t). The Loser (Winner) stocks comprise the bottom (top) quintile of stocks based on the returns in month t. Panel A reports the month $t+1$ (equal-weighted) return for the strategy of going long (short) the Loser (Winner) stocks. The profits are reported for the full sample (1980-2011) as well as two sub-periods: 1980 — 1999 and 2000 — 2011. Risk-adjusted returns are based on a four-factor model comprising the three Fama-French factors (market, size and book-to-market) and the Pastor-Stambaugh liquidity factor. The rows of "Decrease-Increase" report the difference in profits between portfolios with decrease and increase in the number of informed institutions. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Returns to Contrarian Investment Strategies and Change in Number of Informed Institutions									
		Returns				Four-Factor adjusted Returns			
		Firm Size				Firm Size			
Sample Period	ΔInformed_NumInst	Micro	Small	Big	All	Micro	Small	Big	All
1980 — 2011	Decrease	0.898***	0.830***	0.601**	0.796***	0.687***	0.541**	0.319	0.553***
		(4.28)	(3.56)	(2.48)	(4.06)	(3.26)	(2.29)	(1.39)	(2.77)
	Increase	0.317	0.668***	0.247	0.382*	0.132	0.357	-0.059	0.135
		(1.49)	(2.69)	(0.97)	(1.87)	(0.58)	(1.49)	(-0.22)	(0.63)
	Decrease-Increase	0.581***	0.162	0.354*	0.414***	0.555***	0.185	0.377**	0.417***
		(3.71)	(0.91)	(1.94)	(3.78)	(4.01)	(0.98)	(2.23)	(4.14)
1980 — 1999	Decrease	0.885***	1.049***	0.765***	0.858***	0.729***	0.789***	0.525**	0.662***
		(3.40)	(4.02)	(3.30)	(3.95)	(2.75)	(3.03)	(2.28)	(2.94)
	Increase	0.250	0.595**	0.348	0.329	0.103	0.343	0.057	0.134
		(1.15)	(2.33)	(1.33)	(1.57)	(0.44)	(1.31)	(0.20)	(0.61)
	Decrease-Increase	0.635***	0.454**	0.418*	0.530***	0.626***	0.446**	0.468**	0.527***
		(3.32)	(2.22)	(1.75)	(3.69)	(3.84)	(2.01)	(2.03)	(3.96)
2000 — 2011	Decrease	0.916***	0.503	0.355	0.704**	0.857***	0.305	0.247	0.677**
		(2.87)	(1.18)	(0.72)	(1.99)	(2.98)	(0.75)	(0.56)	(2.04)
	Increase	0.417	0.778	0.096	0.462	0.383	0.579	0.001	0.411
		(1.14)	(1.62)	(0.19)	(1.22)	(1.06)	(1.38)	(0.00)	(1.15)
	Decrease-Increase	0.499*	-0.275	0.259	0.241	0.474*	-0.274	0.246	0.266
		(1.91)	(-0.89)	(1.01)	(1.46)	(1.90)	(-0.83)	(1.04)	(1.63)

Table 3: Stock Returns and Institutional Ownership

Stocks are sorted into quintiles according to the three-month ($t-3$ to $t-1$) accumulated stock returns. The Loser (Winner) portfolio comprises the bottom (top) quintile of stocks. Institutional ownership of the stocks is classified into informed and uninformed (Abarbanell, Bushess and Raedy (2003)). Panel A reports the average number of institutions and the percentage of institutional ownership in month $t-1$. Panels B, C and D report the changes in the variables between months $t-3$ and $t-1$, $t-1$ and $t+3$ and between months $t-1$ and $t+6$ respectively. Appendix B provides detailed definitions of the variables. The rows "LMW" report the difference in values between loser and winner portfolios. The sample period is $1980-2011$. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Three-Month Returns and Institutional Ownership

Rank of Past Three-Month Returns	Number of Institutions			Percentage of Institutional Ownership		
	Informed	Uninformed	All	Informed	Uninformed	All
Loser	44.610	33.121	77.731	27.980	13.150	41.130
2	54.867	42.603	97.470	27.224	14.565	41.789
3	58.630	46.107	104.737	27.198	15.029	42.227
4	59.179	45.851	105.030	28.554	15.183	43.737
Winner	48.150	33.919	82.069	29.151	12.957	42.108
LMW	-3.540*	-0.797	-4.337	-1.170**	0.192	-0.978
	(-1.77)	(-0.63)	(-1.36)	(-2.52)	(0.90)	(-1.64)

Panel B: Three-Month Returns and Changes in Institutional Ownership (*t*-1)

Rank of Past Three-Month Returns	Changes in Number of Institutions			Changes in Percentage of Institutional Ownership		
	Informed	Uninformed	All	Informed	Uninformed	All
Loser	-1.743	-0.349	-2.092	-0.360	0.154	-0.206
2	-0.071	0.218	0.146	0.311	0.180	0.491
3	0.970	0.705	1.675	0.519	0.209	0.728
4	2.223	1.293	3.516	0.781	0.309	1.090
Winner	4.194	1.870	6.064	1.541	0.327	1.868
LMW	-5.936***	-2.220***	-8.156***	-1.901***	-0.173***	-2.074***
	(-8.48)	(-9.13)	(-9.03)	(-9.99)	(-4.57)	(-10.68)

Panel C: Three-Month Returns and Changes in Institutional Ownership (*t*+3)

Rank of Past Three-Month Returns	Changes in Number of Institutions			Changes in Percentage of Institutional Ownership		
	Informed	Uninformed	All	Informed	Uninformed	All
Loser	-3.898	-1.557	-5.455	-1.835	-0.450	-2.286
2	-0.289	0.103	-0.186	-0.078	0.028	-0.050
3	1.367	0.915	2.283	0.251	0.127	0.378
4	3.359	1.871	5.230	0.635	0.303	0.938
Winner	5.454	2.494	7.948	1.418	0.298	1.716
LMW	-9.352***	-4.051***	-13.403***	-3.253***	-0.748***	-4.002***
	(-8.29)	(-10.55)	(-9.06)	(-10.33)	(-8.26)	(-11.15)

Panel D : Three-Month Returns and Changes in Institutional Ownership (*t*+6)

Rank of Past Three-Month Returns	Changes in Number of Institutions			Changes in Percentage of Institutional Ownership		
	Informed	Uninformed	All	Informed	Uninformed	All
Loser	-4.751	-2.362	-7.113	-2.545	-0.883	-3.428
2	-0.242	-0.134	-0.376	-0.358	-0.179	-0.536
3	1.712	0.887	2.600	0.070	-0.026	0.044
4	3.830	2.000	5.830	0.418	0.178	0.595
Winner	5.798	2.686	8.484	1.066	0.196	1.263
LMW	-10.549***	-5.048***	-15.597***	-3.611***	-1.079***	-4.691***
	(-8.57)	(-11.62)	(-9.60)	(-10.48)	(-9.88)	(-11.68)

Table 4: Returns to Contrarian Investment Strategies: Sorted by Past Three-Month Returns

Stocks are sorted into three size groups — microcaps, small stocks and big stocks, using NYSE 20th and 50th percentiles as breakpoints. Within each size group, stocks are independently sorted into quintiles according to their lagged three-month accumulated returns ($t-3$ to $t-1$) and one-month returns (t), to generate 25 (5×5) portfolios. The Loser (Winner) portfolio comprises of the bottom (top) quintile of stocks. Panel A reports the month $t+1$ (equal-weighted) profits to the strategy of going long (short) the one-month Loser (Winner) stocks. The profits are reported for the full sample (1980 — 2011, Panel A) as well as two sub-periods: 1980 — 1999 (Panel B) and 2000 — 2011 (Panel C). Risk-adjusted returns are based on a four-factor model comprising the three Fama-French factors (market, size and book-to-market) and the Pástor-Stambaugh liquidity factor. The rows "LMW" report the difference in profits between three-month loser and winner portfolios. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Returns to Contrarian Investment Strategies and Past Three-Month Returns (1980 — 2011)

Rank of Past Three-Month Returns	Returns: Firm Size Micro	Returns: Firm Size Small	Returns: Firm Size Big	Returns: All	Four-Factor adjusted Returns: Firm Size Micro	Four-Factor adjusted Returns: Firm Size Small	Four-Factor adjusted Returns: Firm Size Big	Four-Factor adjusted Returns: All
Loser	1.857***	1.642***	1.038***	1.683***	1.678***	1.345***	0.811***	1.452***
	(8.39)	(5.48)	(3.86)	(7.80)	(7.40)	(4.55)	(3.23)	(6.68)
2	0.490**	0.463*	0.373*	0.442**	0.314	0.201	0.161	0.263
	(2.07)	(1.87)	(1.68)	(2.26)	(1.25)	(0.78)	(0.66)	(1.29)
3	0.218	0.613**	0.402*	0.385**	0.070	0.422*	0.123	0.212
	(1.11)	(2.54)	(1.78)	(2.05)	(0.34)	(1.67)	(0.53)	(1.07)
4	0.006	0.243	0.047	-0.024	-0.205	-0.037	-0.252	-0.256
	(0.03)	(0.94)	(0.18)	(-0.12)	(-0.85)	(-0.13)	(-0.95)	(-1.17)
Winner	-0.282	0.517*	0.017	-0.069	-0.431*	0.252	-0.222	-0.289
	(-1.17)	(1.84)	(0.07)	(-0.32)	(-1.69)	(0.85)	(-0.85)	(-1.26)
LMW	2.139***	1.126***	1.021***	1.752***	2.109***	1.093***	1.034***	1.741***
	(7.30)	(3.81)	(3.58)	(7.46)	(7.12)	(3.58)	(4.02)	(7.55)

Panel B: Returns to Contrarian Investment Strategies and Past Three-Month Returns (1980 — 1999)

Rank of Past Three-Month Returns	Returns: Firm Size Micro	Returns: Firm Size Small	Returns: Firm Size Big	Returns: All	Four-Factor adjusted Returns: Firm Size Micro	Four-Factor adjusted Returns: Firm Size Small	Four-Factor adjusted Returns: Firm Size Big	Four-Factor adjusted Returns: All
Loser	2.240***	1.918***	1.479***	2.010***	2.100***	1.720***	1.339***	1.844***
	(8.69)	(5.47)	(5.86)	(8.23)	(7.85)	(4.95)	(4.96)	(7.45)
2	0.466	0.642**	0.664***	0.523**	0.316	0.392	0.523**	0.368
	(1.64)	(2.20)	(2.92)	(2.28)	(1.08)	(1.33)	(2.08)	(1.62)
3	0.023	0.790***	0.593**	0.295	-0.037	0.695**	0.357	0.162
	(0.10)	(2.95)	(2.41)	(1.41)	(-0.16)	(2.55)	(1.34)	(0.77)
4	-0.244	0.457*	0.242	0.010	-0.381	0.208	0.018	-0.120
	(-1.00)	(1.74)	(0.91)	(0.05)	(-1.43)	(0.74)	(0.07)	(-0.54)
Winner	-0.510**	0.277	0.104	-0.251	-0.637***	0.058	-0.049	-0.420*
	(-2.12)	(0.86)	(0.37)	(-1.14)	(-2.60)	(0.17)	(-0.17)	(-1.85)
LMW	2.750***	1.641***	1.374***	2.261***	2.738***	1.662***	1.387***	2.263***
	(8.85)	(4.68)	(4.15)	(8.62)	(8.95)	(4.68)	(4.35)	(9.23)

Panel C: Returns to Contrarian Investment Strategies and Past Three-Month Returns (2000 — 2011)

Rank of Past Three-Month Returns	Returns: Firm Size Micro	Returns: Firm Size Small	Returns: Firm Size Big	Returns: All	Four-Factor adjusted Returns: Firm Size Micro	Four-Factor adjusted Returns: Firm Size Small	Four-Factor adjusted Returns: Firm Size Big	Four-Factor adjusted Returns: All
Loser	1.221***	1.183**	0.302	1.139***	1.221***	1.027*	0.488	1.254***
	(3.22)	(2.21)	(0.54)	(2.91)	(3.08)	(1.86)	(1.13)	(3.02)
2	0.531	0.164	-0.112	0.308	0.447	0.184	-0.038	0.357
	(1.41)	(0.37)	(-0.25)	(0.92)	(1.14)	(0.40)	(-0.07)	(1.08)
3	0.542*	0.317	0.083	0.536	0.517	0.250	0.033	0.568
	(1.72)	(0.72)	(0.20)	(1.55)	(1.50)	(0.58)	(0.09)	(1.52)
4	0.423	-0.114	-0.277	-0.081	0.290	-0.312	-0.417	-0.189
	(1.12)	(-0.23)	(-0.53)	(-0.22)	(0.82)	(-0.73)	(-0.94)	(-0.57)
Winner	0.098	0.916*	-0.129	0.236	0.118	0.841	-0.313	0.194
	(0.22)	(1.80)	(-0.27)	(0.58)	(0.25)	(1.53)	(-0.74)	(0.46)
LMW	1.122**	0.267	0.432	0.903**	1.103**	0.187	0.801*	1.060**
	(2.14)	(0.54)	(0.92)	(2.32)	(2.00)	(0.34)	(1.79)	(2.37)

Table 5: Returns to Industry-Adjusted Contrarian Investment Strategies: Sorted by Past Three-Month Returns

Stocks are sorted into three size groups ─ microcaps, small stocks and big stocks, using NYSE 20th and 50th percentiles as breakpoints. Within each size group, stocks are independently sorted into quintiles according to their lagged three-month accumulated returns ($t-3$ to $t-1$) and one-month industry-adjusted returns (t), to generate 25 (5×5) portfolios. The Loser (Winner) portfolio comprises of the bottom (top) quintile of stocks. Panel A reports the month $t+1$ (equal-weighted) profits to the strategy of going long (short) the one-month Loser (Winner) stocks. The profits are reported for the full sample (1980 ─ 2011, Panel A) as well as two sub-periods: 1980 ─ 1999 (Panel B) and 2000 ─ 2011 (Panel C). Risk-adjusted returns are based on a four-factor model comprising the three Fama-French factors (market, size and book-to-market) and the Pástor-Stambaugh liquidity factor. The rows "LMW" report the difference in profits between three-month loser and winner portfolios. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Returns to Industry-Adjusted Contrarian Investment Strategies Sorted by Size and Past Three-Month Returns

Rank of Past Three-Month Returns	Returns				Four-Factor adjusted Returns			
	Firm Size			All	Firm Size			All
	Micro	Small	Big		Micro	Small	Big	
Panel A: 1980 ─ 2011								
Loser	2.382***	1.953***	1.289***	2.018***	2.232***	1.665***	1.082***	1.816***
	(11.02)	(7.02)	(5.31)	(9.98)	(10.06)	(6.21)	(5.01)	(9.10)
Winner	0.220	0.873***	0.282	0.381**	0.102	0.647***	0.081	0.219
	(1.13)	(3.83)	(1.53)	(2.33)	(0.51)	(2.62)	(0.43)	(1.27)
LMW	2.162***	1.080***	1.007***	1.636***	2.129***	1.018***	1.002***	1.598***
	(8.10)	(3.90)	(4.09)	(7.64)	(8.07)	(3.59)	(4.22)	(7.77)
Panel B: 1980 ─ 1999								
Loser	2.687***	2.193***	1.800***	2.355***	2.553***	1.994***	1.582***	2.169***
	(10.50)	(6.59)	(7.23)	(10.07)	(9.85)	(5.97)	(6.22)	(9.37)
Winner	0.118	0.779***	0.369*	0.276	0.002	0.558**	0.201	0.111
	(0.59)	(2.97)	(1.81)	(1.65)	(0.01)	(2.03)	(1.00)	(0.66)
LMW	2.569***	1.414***	1.430***	2.079***	2.550***	1.436***	1.381***	2.058***
	(8.93)	(4.15)	(5.35)	(8.56)	(9.24)	(4.20)	(5.12)	(9.11)
Panel C: 2000 ─ 2011								
Loser	1.873***	1.552***	0.438	1.457***	1.829***	1.288***	0.627*	1.530***
	(4.99)	(3.18)	(0.96)	(4.12)	(4.54)	(2.65)	(1.90)	(4.09)
Winner	0.389	1.030**	0.136	0.558*	0.370	1.005*	0.059	0.537
	(1.04)	(2.40)	(0.38)	(1.72)	(0.91)	(1.95)	(0.16)	(1.48)
LMW	1.484***	0.523	0.302	0.899**	1.459***	0.283	0.568	0.993***
	(3.00)	(1.14)	(0.68)	(2.52)	(2.81)	(0.56)	(1.42)	(2.64)

Table 6: Returns to Contrarian Investment Strategies: Sorted by Past Quarterly Returns

At the end of each month t, stocks are independently sorted into quintiles according to their accumulated three-month returns in $t-4$ (i.e., $t-6$ to $t-4$), in $t-1$ ($t-3$ to $t-1$) and one-month return (t). The Loser (Winner) portfolio comprises of the bottom (top) quintile of stocks. Panel A reports, for each of the 25 (5×5) portfolios sorted by immediate past three-month returns and the previous three-month returns, the equal-weighted risk-adjusted return in month $t+1$ to the strategy of going long (short) the one-month Loser (Winner) stocks. The profits are reported for the full sample (1980 ─ 2011, Panel A) as well as two sub-periods: 1980 ─ 1999 (Panel B) and 2000 ─ 2011 (Panel C). Risk-adjusted returns are based on a four-factor model comprising the three Fama-French factors (market, size and book-to-market) and the Pástor-Stambaugh liquidity factor. The rows "LMW" report the difference in profits between three-month loser and winner portfolios. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Four-Factor adjusted Returns to Contrarian Investment Strategies Sorted by Past Returns (1980 ─ 2011)						
Rank of Past Three-Month Returns	Rank of Past Four to Six-Month Returns					LMW
	Loser	2	3	4	Winner	
Loser	2.202***	1.644***	1.510***	1.222***	0.714***	1.488***
	(7.23)	(5.89)	(5.17)	(4.30)	(3.02)	(5.04)
2	1.032***	0.669***	0.657***	0.032	-0.203	1.235***
	(3.34)	(2.72)	(2.70)	(0.15)	(-0.71)	(3.68)
3	0.745***	0.253	0.151	0.317	-0.016	0.760**
	(2.70)	(1.00)	(0.66)	(1.28)	(-0.05)	(2.33)
4	0.029	-0.454*	0.124	-0.091	-0.386	0.415
	(0.13)	(-1.76)	(0.50)	(-0.36)	(-1.40)	(1.39)
Winner	-0.312	-0.247	-0.273	0.127	-0.203	-0.110
	(-1.18)	(-0.82)	(-1.00)	(0.48)	(-0.74)	(-0.37)
LMW	2.515***	1.892***	1.783***	1.095***	0.917***	
	(7.52)	(5.34)	(4.82)	(3.30)	(3.01)	
Panel B: Four-Factor adjusted Returns to Contrarian Investment Strategies Sorted by Past Returns (1980 ─ 1999)						
Rank of Past Three-Month Returns	Rank of Past Four to Six-Month Returns					LMW
	Loser	2	3	4	Winner	
Loser	2.921***	2.025***	1.849***	1.464***	0.787***	2.133***
	(8.63)	(6.39)	(5.57)	(4.54)	(2.66)	(6.69)
2	1.241***	0.804***	0.894***	0.103	-0.085	1.327***
	(4.07)	(2.75)	(2.86)	(0.39)	(-0.29)	(4.06)
3	0.991***	0.478	-0.178	0.429	-0.249	1.240***
	(3.10)	(1.46)	(-0.59)	(1.60)	(-0.76)	(3.29)
4	0.195	-0.369	0.245	-0.043	-0.289	0.484
	(0.82)	(-1.46)	(0.94)	(-0.15)	(-0.97)	(1.48)
Winner	-0.369	-0.455	-0.405	0.014	-0.381	0.012
	(-1.16)	(-1.58)	(-1.37)	(0.05)	(-1.33)	(0.04)
LMW	3.289***	2.480***	2.254***	1.450***	1.168***	
	(8.06)	(7.33)	(5.99)	(3.60)	(3.48)	
Panel C: Four-Factor adjusted Returns to Contrarian Investment Strategies Sorted by Past Returns (2000 ─ 2011)						
Rank of Past Three-Month Returns	Rank of Past Four to Six-Month Returns					LMW
	Loser	2	3	4	Winner	
Loser	1.544***	1.380**	1.373**	1.269**	0.920**	0.625
	(2.80)	(2.31)	(2.47)	(2.48)	(2.08)	(1.08)
2	0.845	0.570	0.545	0.139	0.040	0.806
	(1.39)	(1.36)	(1.39)	(0.41)	(0.08)	(1.32)
3	0.695	0.177	0.777**	0.309	0.720	-0.025
	(1.32)	(0.45)	(2.07)	(0.65)	(1.57)	(-0.04)
4	-0.045	-0.231	0.343	0.168	-0.319	0.275
	(-0.11)	(-0.55)	(0.81)	(0.39)	(-0.70)	(0.52)
Winner	0.135	0.143	0.320	0.640	0.263	-0.128
	(0.34)	(0.23)	(0.70)	(1.20)	(0.47)	(-0.22)
LMW	1.409**	1.237	1.052	0.629	0.657	
	(2.37)	(1.60)	(1.54)	(1.15)	(1.00)	

Table 7: Returns to Contrarian Investment Strategies: Control for Illiquidity and Volatility

At the end of each month t, stocks are independently sorted into quintiles according to their lagged three-month ($t-3$ to $t-1$) accumulated stock returns, stock illiquidity (or return volatility) and their one-month returns (t). The Loser (Winner) portfolio comprises of the bottom (top) quintile of stocks. Panel A reports, for each of the 25 (5×5) portfolios sorted by past three-month returns and the average three-month Amihud illiquidity ($t-3$ to $t-1$), the equal-weighted return in month $t+1$ to the strategy of going long (short) the one-month Loser (Winner) stocks. Risk-adjusted returns are based on a four-factor model comprising the three Fama-French factors (market, size and book-to-market) and the Pástor-Stambaugh liquidity factor. The profits are reported for the full sample from 1980 to 2011. Panel B reports similar statistics when the 25 (5×5) portfolios sorted by past three-month returns and the three-month daily stock return volatility ($t-3$ to $t-1$). The row "LMW" reports the difference in profits between three-month loser and winner portfolios. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Returns to Contrarian Investment Strategies Sorted by Past Three-Month Returns and Amihud Illiquidity

Rank of Past Three-Month Returns	Returns					Four-Factor adjusted Returns				
	Rank of Amihud Illiquidity					Rank of Amihud Illiquidity				
	Liquid	2	3	4	Illiquid	Liquid	2	3	4	Illiquid
Loser	0.650*	1.578***	1.564***	1.921***	2.479***	0.416	1.327***	1.320***	1.751***	2.433***
	(1.87)	(5.14)	(5.11)	(7.26)	(7.44)	(1.19)	(4.27)	(4.14)	(6.64)	(7.57)
2	0.146	0.231	0.286	0.479	1.116***	-0.039	0.020	0.065	0.375	1.029***
	(0.53)	(0.89)	(1.03)	(1.58)	(3.82)	(-0.13)	(0.07)	(0.22)	(1.18)	(3.65)
3	0.353	0.382	0.166	0.112	0.750**	0.119	0.109	0.093	-0.016	0.638**
	(1.27)	(1.38)	(0.56)	(0.43)	(2.47)	(0.43)	(0.38)	(0.30)	(-0.06)	(2.04)
4	-0.152	-0.045	-0.299	-0.292	0.498*	-0.536*	-0.286	-0.506*	-0.395	0.342
	(-0.51)	(-0.15)	(-1.13)	(-1.20)	(1.87)	(-1.80)	(-0.88)	(-1.82)	(-1.55)	(1.25)
Winner	-0.195	0.061	0.121	-0.261	0.221	-0.542	-0.178	-0.126	-0.500	0.206
	(-0.60)	(0.22)	(0.44)	(-0.86)	(0.76)	(-1.63)	(-0.62)	(-0.41)	(-1.55)	(0.70)
LMW	0.845**	1.517***	1.442***	2.182***	2.258***	0.958**	1.505***	1.446***	2.251***	2.227***
	(2.08)	(4.51)	(4.05)	(5.77)	(5.60)	(2.43)	(4.47)	(4.02)	(5.88)	(5.78)

Panel B: Returns to Contrarian Investment Strategies Sorted by Past Three-Month Returns and Return Volatility

Rank of Past Three-Month Returns	Returns					Four-Factor adjusted Returns				
	Rank of Return Volatility					Rank of Return Volatility				
	Low	2	3	4	High	Low	2	3	4	High
Loser	0.739**	1.438***	1.707***	1.392***	2.202***	0.484	1.216***	1.450***	1.064***	2.021***
	(2.02)	(5.12)	(7.22)	(5.39)	(7.38)	(1.22)	(4.43)	(6.33)	(4.02)	(6.64)
2	0.486**	0.888***	0.757***	0.377	0.441	0.289	0.616***	0.533**	0.137	0.504
	(2.28)	(3.74)	(3.22)	(1.46)	(1.35)	(1.43)	(2.84)	(2.33)	(0.50)	(1.42)
3	0.473*	0.765***	0.563***	0.458	0.722**	0.276	0.555**	0.416*	0.290	0.632*
	(1.87)	(3.57)	(2.59)	(1.59)	(2.16)	(1.13)	(2.50)	(1.89)	(0.98)	(1.68)
4	0.283	0.644***	0.106	0.020	-0.255	-0.024	0.397*	-0.166	-0.153	-0.347
	(1.26)	(3.22)	(0.42)	(0.08)	(-0.81)	(-0.10)	(1.83)	(-0.62)	(-0.64)	(-1.05)
Winner	-0.038	0.685**	0.244	-0.008	-0.350	-0.140	0.460*	0.060	-0.282	-0.495*
	(-0.10)	(2.57)	(1.10)	(-0.03)	(-1.33)	(-0.35)	(1.67)	(0.26)	(-1.17)	(-1.83)
LMW	0.777	0.754**	1.463***	1.401***	2.552***	0.624	0.756**	1.390***	1.345***	2.517***
	(1.50)	(2.07)	(4.91)	(4.55)	(7.67)	(1.13)	(2.13)	(4.82)	(4.39)	(7.49)